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THESIS

AN ANALYSIS OF THE PREDICTION ACCURACY OF THE U.S. NAVY REPAIR TURN-AROUND TIME FORECAST MODEL

by

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June 2003

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This thesis examines the forecast accuracy of repair times for a subset of repairable U.S Navy inventory items. Forecasts are currently calculated using the Uniform Inventory Control Program (UICP) on a quarterly basis. The UICP model use the time of repairs completed in the current quarter to update a "file" value in order to forecast the repair times for the following quarter. Forecasts are calculated separately for repairable items grouped into families. This thesis demonstrates that aggregation repairs by their completion dates, as currently done by the UICP model, causes forecast to be affected by the nature of the repair arrival process. The more that this process differs from a Poisson process, the more that the forecast values are affected. Using bootstrap simulations, the effect of the repair process on the forecasting is quantified. This thesis also explores alternatives to the UICP model for forecasting repair times. In particular, an approach that utilizes repairs that have not been completed by the end of the current quarter is developed.

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This thesis examines the forecast accuracy of repair times for a subset of repairable U.S Navy inventory items. Forecasts are currently calculated using the Uniform Inventory Control Program (UICP) on a quarterly basis. The UICP model use the time of repairs completed in the current quarter to update a “file” value in order to forecast the repair times for the following quarter. Forecasts are calculated separately for repairable items grouped into families. This thesis demonstrates that aggregation repairs by their completion dates, as currently done by the UICP model, causes forecasts to be affected by the nature of the repair arrival process. The more that this process differs from a Poisson process, the more that the forecast values are affected. Using bootstrap simulations, the effect of the repair process on the forecasting is quantified. This thesis also explores alternatives to the UICP model for forecasting repair times. In particular, an approach that utilizes repairs that have not been completed by the end of the current quarter is developed.

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LIST OF ACRONYMS

APA	Appropriation Purchase Account
ASD	Aviation Supply Division
AVLDR	Aviation Depot Level Repair
CBO	Congressional Budget Office
DBOF	Defense Business Operating Funds
DLR	Depot Level Repair
DOP	Designated Overhaul Point
DSP	Designated Support Point
FLR	Field Level Repair
IMA	Intermediate Maintenance Activity
LRCA	Local Repair Cycle Assets
NAVICP-Phi	Naval Inventory Control Point, Philadelphia
NIIN	National Item Identification Number
NRFI	Non Ready-for-Issued
RFI	Ready-for-Issued
RTAT	Repair Turn-Around Time
SSC	Supply Support Center
UICP	Uniform Inventory Control Program

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EXECUTIVE SUMMARY

The United States Navy manages an extensive inventory of items in order to maintain the readiness of its forces. In order to manage its inventory in a cost-effective manner, the Navy must determine the quantities of each type of item that it must keep in stock. Overspending on one item diverts resources from other items. Many items in the Naval inventory provide material to inventory through the repair of units when the cost of repair is less than the cost purchasing new units. For repairable items, the inflow of material to inventory therefore consists of two sources: newly purchased material, and repaired material. If the quantity of repaired material can be accurately forecast, requirements for newly purchased material can be minimized, thereby allowing for better management of the inventory management resources.

To efficiently manage its inventory, the Naval Inventory Control Point (NAVICP) developed the Uniform Inventory Control Program (UICP) in the 1960s. One component of this program is a repair turn-around time (RTAT) forecast model that uses a common methodology across all items. The RTAT forecast model uses repairs that have been completed in the current quarter to update a “file” forecast value for each item, in order to predict repair times for the following quarter. This aggregation of repairs by completion time has several noteworthy features: (1) it does not make use of repairs that were initiated during the current or earlier quarters that and not been completed before the end of the current quarter; (2) it is affected by the nature of the arrival process for repairs.

For example, if no repairs were initiated during the last three quarters, then any repair that was completed during the current quarter must have taken at least 270 days.

Due to the aggregation of repairs by their completion dates, UICP forecasts may fluctuate even if the repair process itself is stable. One objective of this thesis is to quantify the effect of the arrival process of repairs on the RTAT forecast. This is done by considering a subset of fifteen repairable items that have both high monetary values and high frequencies of repairs. Data on repairs were obtained for a seven-year period encompassing calendar years 1996 through 2002. For a given item, a simulation experiment was conducted wherein the arrival times of repairs were treated as fixed, and bootstrap samples of the repair times were randomly allocated to them. The between-quarters standard deviation (SD) of mean repair times was calculated, and compared to the between-quarters SD obtained in a similar manner for arrival times that were generated from a Poisson process. The ratio of the two between-quarters SDs is used to demonstrate the effect of the arrival process on mean repair times aggregate by their completion dates.

For the fifteen items that were considered in the thesis research, the SD ratio ranged from 1.13 to 5.91, with a median of 1.85. Much of the variability that affects the current RTAT forecast methodology is therefore due to the nature of the arrival process, in contrast to the repair process itself. It is also shown that as the arrival process diverges from a Poisson process, the ratio of the between-quarter SDs typically increases.

This thesis also explores other aspects of the current RTAT forecast model that affects its forecast accuracy. The current model uses an outlier exclusion criterion that rejects repair times that are either too high or too low relative to the interquartile spread of the data. However, it is shown that the repair times have strongly right-skewed distributions, with the effect that the outlier exclusion criterion overwhelmingly rejects as outliers observations that are too large rather than too small. This one-side rejection behavior can impart bias to the forecast values. It is shown that the logarithms of repair times have distributions that are more symmetric, which suggests that forecasting based on the logarithm may produce more satisfactory results.

Finally, this thesis explores an alternative to the current forecast methodology, by aggregating repair times by their quarter of induction instead of their quarter of completion. Induction-based aggregation requires that repairs that have not been completed be included as right-censored values. Although the presence of censored data makes forecasting more complicated than under completion-based aggregation, induction-based aggregation is not affected by the arrival process, and it may be more useful for predicting the state of the repair process when a repair has been initiated. This thesis proposes a methodology, based on survival analysis, for using censored repair times to predict the state of the repair process in the following quarter.

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I. INTRODUCTION

A. BACKGROUND

The U.S. Navy has limited resources, as does any other organization. After the Cold War, U.S. military policy changed because of the collapse of the Soviet Union, and the strategic role of the Navy changed at the same pace. The missions changed and increased while the resources available for these missions were reduced by about 35 percent, and the estimated funding level for the Navy through 2020 is roughly US $90 billion (percentage and budget adjusted for inflation). In October 2000, studies conducted by the Congressional Budget Office (CBO) warned the government to difficulties the Navy was facing in keeping its level of readiness, updating materiel and providing quality of life for its personnel.

The Navy has begun efforts to maintain its level of readiness at the lowest cost. The main factors in the Navy’s annual budget can be categorized as materiel and personnel costs. Materiel costs include acquisition and maintenance, with maintenance cost of aviation assets being one of the largest. The Navy has developed systems such as the Uniform Inventory Control Program (UICP), funded research, and stimulated the development of new procedures to predict the behavior of aviation materiel, and its repair, and to improve acquisition procedures while attempting to keep the same level of efficacy. Therefore, the Navy’s task is to find better measures to support the decision makers, particularly for the acquisition of repair parts at Depot level, as part of the Navy supply system.

The U.S. Navy has a very complex supply system. What follows is a brief view of how the repair process works at the Depot level. This will facilitate understanding and discussion of the issues in this thesis.

The U.S. Navy supply system is responsible for procuring, maintaining, and distributing equipment, repair parts, and consumable items to support Naval operations. Management of the Naval inventory system is the responsibility of the Naval Inventory Control Point (NAVICP). Advancing technologies and changing operational requirements have imposed a constant adaptability into the supply system to provide adequate support, especially for aviation materiel. The Navy Inventory Control Point-Philadelphia (NAVICP-Phi) has primary responsibility for maintaining inventories related to Naval aviation, but also is responsible for parts related to power plants, avionics, meteorology and safety, to name a few.

Each Naval inventory item is classified as repairable or consumable. For aviation items, repairable items are further classified either as Aviation Depot Level Repairable (AVDLR) or Depot Level Repairable (DLR). DLR items represent the larger dollar investment in the aviation inventory (Nonresident Training Course, 1996). Improving the management of these items will increase the readiness of the Navy and reduce the cost of its supply system, since aviation represents the greatest cost of the entire Naval supply system.

Another classification, related to usefulness, distinguishes between items that are serviceable or unserviceable. Serviceable items, when economically repairable, are sent to field-level repair (FLR) or depot-level repair facilities, and are designated as “not ready for issue” (NRFI) until repairs are completed.

NAVICP maintains records of repairable components. The system uses the data to match procurement and distribution, to keep an adequate workload for scheduling repairs, and to achieve a desired ready for issue (RFI) level of stocks. Based on the amount of RFI and NRFI material for a particular inventory item, the item manager must decide on the quantities of that item to buy or repair NRFI in order to maintain an adequate inventory level. This is a significant management decision because the repair cost is usually much lower than the cost of buying a new item (Maher, 1993).

Funding of the repair system comes from the Defense Business Operation Funds (DBOF), Appropriation Purchase Accounts (APA), contractor-supported funds, and end users (both onshore and afloat). Figure 1 illustrates the DBOF cash cycle.

When an item becomes unserviceable, the item manager examines the quantities of RFI and NRFI material for that item in order to decide whether to buy new material from the vendor or to send the item to a repair facility and wait until a repaired item becomes RFI. Eventually, an RFI item is returned to the inventory shelf. When a user requests the item, material is issued from inventory and the system is reimbursed by the customer’s operating funds.

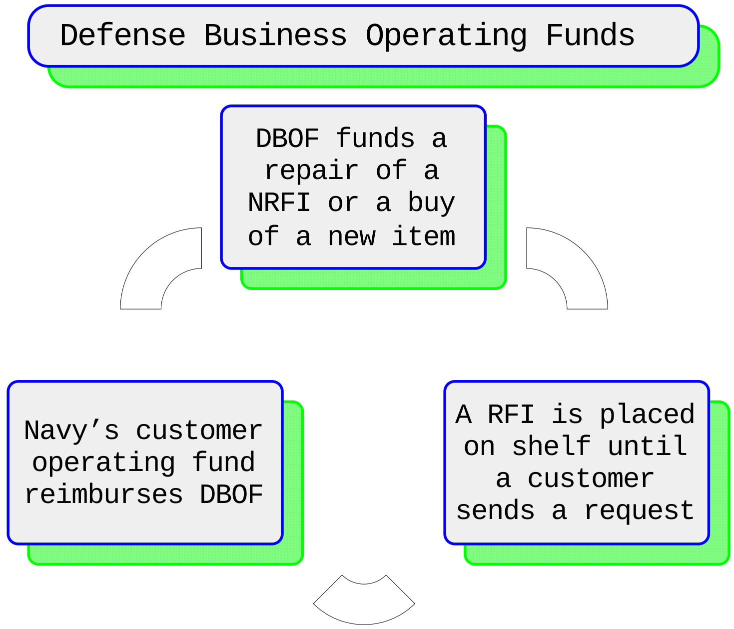

Figure 1. Cash Cycle for Defense Business Operating Funds Acquisition of Material.

NAVICP-Phi grants a fixed number of allowances (RFI placed on shelf) to be held at local repair cycle assets (LRCA) under Aviation Supply Division or Supply Support Center (ASD/SSC). The LRCA receives, stores, issues and accounts for repairable assets controlled by ASD/SSC. Each time a NRFI item is removed from an aircraft or from other equipment, LRCA replaces it by a RFI item. If the NRFI item cannot be repaired locally it is forward to the I-level repair system, from which it is sent to the designated repair point (DSR) or designated support point (DSP) for repair. This action places an item in the repair system, and it generates a requisition for a RFI replacement. The supply system has to provide a replacement for the requisitioned item.

The number of allowances is fixed, based on failure rates and the I-level repair turn-around time (RTAT). RTAT is the total amount of time it takes to conduct the repair of a NRFI item and return it to the shelf in RFI condition. This is the most important reason that NAVICP attempts to keep RTAT as low as possible.

B. PROBLEM STATEMENT

The main cost of the Naval supply system is with aviation supply. The Navy must have a good estimator of RTAT to support item managers in their decisions either to buy new material or to expect delivery of RFI material from the repair system. Today, the main instrument used by the officers at NAVICP-Phi is the RTAT forecast obtained from the UICP. A more accurate forecast of RTAT will enable the Navy to reduce its inventory costs and improve its supply system readiness.

C. RESEARCH OBJECTIVES

The aims of the thesis research are as follows:

1. Develop an understanding of the Naval repair system, using the data available.

2. Assess the validity of the assumptions for the UICP model as it relates to the forecasting of RTAT.

3. Evaluate possible alternatives for the forecasting of repair turn-around times, using information in the repair system that is not currently being used.

D. RESEARCH QUESTIONS

The following research questions will be addressed:

1. NAVICP-Phi uses data of the repair completed in one quarter to forecast RTAT values for the following quarter.

Which probabilistic assumptions are valid for the RTAT to make these forecasts reasonable?

2. Decision makers at NAVICP base procurement decisions on RTAT forecasts. If forecasts were modified to utilize information available to the system that is not currently being used, such as repairs in progress, how much better would the forecasts be?

3. The current UICP forecast is oriented towards predicting the amount of time that an item was under repair, given that the repair is completed “now”. In other words, it characterizes the past, rather than the future, of the repair process. Generally, it is not the same as predicting the amount of time needed to repair an item, given that it is inducted into the repair system “now”. Is the current RTAT forecast methodology, based on an appropriate measure of performance for the Naval inventory repair system?

E. METHODOLOGY OVERVIEW

The thesis research uses statistical techniques for data description, for developing estimators, for measuring the accuracy of forecasts, and for evaluating assumptions about the distribution of repair times. Simulation is used to conduct a numerical evaluation of the forecasts.

In order to formulate assumptions about the RTAT distribution, it is important to recognize that repairs are subject to scheduling, that they are sent to repair in batches, and that there are fluctuations over time in the demand for RFI material. However, in some cases the use of a distribution having a simple form can make great improvements in estimation. In other cases, when the original data does not fit the required assumptions about a theoretical distribution, transformation of the data can improve the analysis. At the end of the analysis, the data is transformed back to its original range. Some transformations work better for some situations depending on the skewness of the data. The most used transformations are power transformations and logarithms (Devore, 2000). The first step toward analysis in many fields uses the natural logarithm of the data.

Visualization of the transformation through quantile-quantile (QQ) plots and histograms is often a useful way to select the best transformation of a set of data. Usually, the assumptions about the distributions of the sample are checked using QQ plots or histograms (Hamilton, 1992).

Simulation typically is used when the decision-maker has to choose among alternative configurations of a system and the behavior of the system is random in some respect. Another possible application for simulation is to evaluate numerically the behavior of a particular system. Cases like this occur often in real-word problems where assumptions of specific distribution or its parameters are not reasonable for the analysis. The use of bootstrapping, a process of random resampling of the data with replication, can allow analysis without the imposition of restrictive assumptions about the data. In particular, this research will use bootstrapping to estimate quantities of interest and to test hypotheses.

A tool commonly used for describing a system and ultimately setting up a simulation is the event graph (EG) because the update of the state variables of a system is driven by events. EG is a simple and powerful tool for describing processes. An EG has a set of nodes, representing the events or state transitions, a set of state variables, and a set of arcs. These arcs represent alternative decisions, which might be a boolean condition with or without delay time (Law and Kelton, 2000). A system such as the repair process can be modeled using discrete EG.

Figure 2 describes in general terms the flow of a repair and the alternatives that NAVICP-Phi uses for maintaining an adequate level of allowances or number of RFI at the Local Repair Cycle Assets (LRCA).

A NRFI event starts the repair cycle. It updates the state variables of the system increasing the number of NRFI at LRCA. LRCA will forward the NRFI to the intermediate maintenance activity (IMA); at the same time, a RFI replaces a NRFI, decreasing the number of RFI at LRCA. The NRFI inducted at the IMA can be repaired and returned to LRCA or be forwarded to a designated support point (DSP) for repair; in this case, a replacement unit is requested from the supply system (NAVICP-Phi). At this point, the NAVICP-Phi will have two alternatives: the first is to back order, skip a buy, and wait for a repair completion; the second is to buy an item and immediately fulfill the demand. In either case, the number of NRFI decreases and the number of RFI increases at LCRA. The main instrument the NAVICP-Phi uses to establish the allowance level at LRCA is the RTAT.

The highlighted portion of this EG relates to the data available for the analysis in this thesis; particularly, repair turn-around time (RTAT) incorporates the time when the item was inducted into DSP until it returns to a RFI condition (administrative time—t_{adm}—plus repair time—t_{repair}). The entire cycle is known as the Depot Repair Cycle (NAVSUP, 1992).

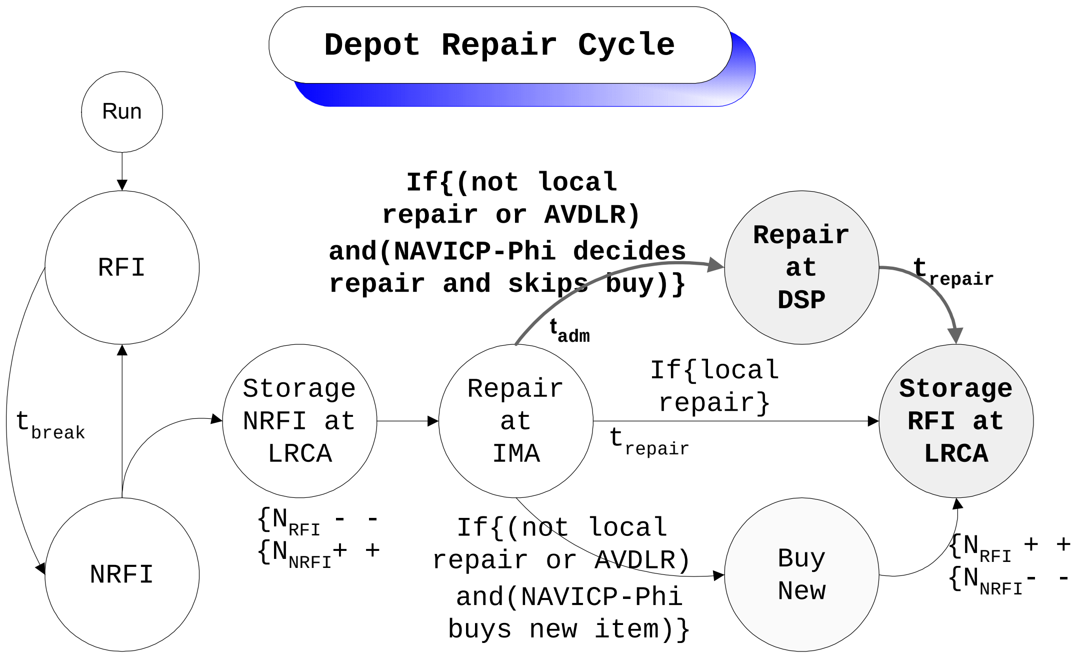

Figure 2. Event Graph of Repair Process at Depot Level.

F. DATA USED FOR RESEARCH

The data used in the thesis research were obtained from NAVICP-Phi, covering a seven-year period from 1996 through 2002. These data provide repair times and other descriptive information concerning all repairs of Naval inventory items that were completed during that period of time. A fuller description of the data is provided in Chapter II of this thesis.

G. SCOPE AND LIMITATION

NAVICP manages about 350,000 line items in its inventory (Harnitcek, 2002). The complexity of the Navy supply system restricts this research to the analysis of one group of repairable items: the fifteen items considered by Ropiak (2000) with high monetary value and high frequency of repair.

Each Naval inventory item has its own identification. The National Item Identification Number (NIIN) uniquely identifies all items. Appendix A provides a table with all NIIN together with names and descriptions of the NIIN used in this research.

II. DATA ANALYSIS

NAVICP-Phi provided data comprising calendar years 1996 (first quarter) through 2002 (third quarter); also, it provided UICP quarterly forecast estimates for repair times, by item, for the period comprising calendar years 1995 (third quarter) through 2002 (third quarter). The observed and forecast data overlaps over the interval 1996 (first quarter) and 2002 (third quarter), encompassing 28 quarters of forecast and observations.

A. REPAIR TURN-AROUND TIME DATA

Repair turn-around time (RTAT) is the lapsed time from when an item is inducted into the repair system until it is returned in ready-for-issue (RFI) condition. RTAT includes all delays in the system, such as administrative time, days waiting for parts, time waiting in the repair queue, and transportation time, in addition to time required to complete the physical repair. Each database contains the repair time, the completion date, the designated overhaul point (DOP) that performed the repair, and the quantity in each batch that was sent to the repair system as a group.

The following criteria were used to exclude records from the analysis:

1. RTAT values less than 4 days or greater than 998, which were potentially erroneous (Jacoby, 1999).

2. RTAT values that were inflated due to days waiting for parts, which idled the repair process.

In order to ensure enough data for analysis, we limited our considerations to items that had at least 100 completed repairs over the period of interest. Ultimately, our analysis focuses on the set of fifteen Naval repairable items identified in Ropiak (2000) that had both high repair rates and high monetary value.

B. DISTRIBUTION OF RTAT

Table 1 provides the number of repairs by length of repair in days per batch size. It is clear that, for the fifteen repairable items considered in this thesis, most repairs were completed within one quarter (approximately 90 days).

LENGTH OF REPAIR TIME (RTAT) IN DAYS	BATCH SIZE			
	1	2	3	4+
0 – 29	5014	1345	451	839
30 – 59	3670	889	258	523
60 – 89	1651	342	113	263
90 – 119	825	136	53	148
120 – 149	308	53	25	50
+ 150	704	61	24	38

Table 1. Frequency Analysis of RTAT for Fifteen Selected Items.

Figure 3 shows the histograms and quantile-quantile (QQ) plots for the RTAT value for two items that had the greatest number of repairs during the time frame of interest, and illustrates the general distribution characteristics of repair-time data. It can be seen that the distribution is markedly skewed. Appendix C provides a full collection of histograms and QQ plots of the fifteen-item data set.

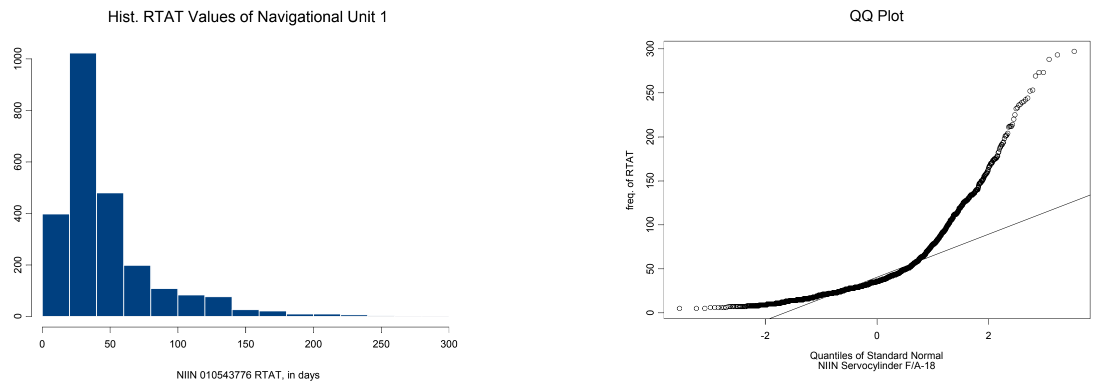

Figure 3. Histogram and QQ-Plot of Servocylinder RTAT Value.

C. DISTRIBUTION OF THE INTERARRIVAL REPAIR TIMES

Interarrival time for repairs is the lapsed time between successive arrivals into the repair process. The completion time minus RTAT constitutes the arrival time. Table 2 provides the mean interarrival times of repairs in at DOPs for two items that had the greatest and the least number of repairs in the data set for analysis. The rates will vary largely between interarrivals in DOPs as a function of the number of repairs performed in each facility.

REPAIRABLE ITEM	NUMBER OF REPAIRS	MEAN INTERARIVAL TIME IN DAYS
Servocylinder F/A-18	2464	1.075
Actuator assembly F404	577	3.086

Table 2. Mean Interarrival Time and Count of Repairable Items between 1996 (1^{st} Quarter) and 2002 (3^{rd} quarter) in the Fifteen Selected Items.

Figure 4 displays the cumulative iterarrival times for the Starter engine CH-46E. These interarrival items have a fairly stationary increment over time, conditioning on the number of repairs, which gives rise to the assumption of independent increment of the arrivals, one of the basic definitions of a Poisson process (Ross, 2000). This same behavior was observed for the other items. Figure 5, displays the histograms for the mean interarrival time and the count of the number of repairs for the same item, which suggests some cyclic behavior that would invalidate this assumption.

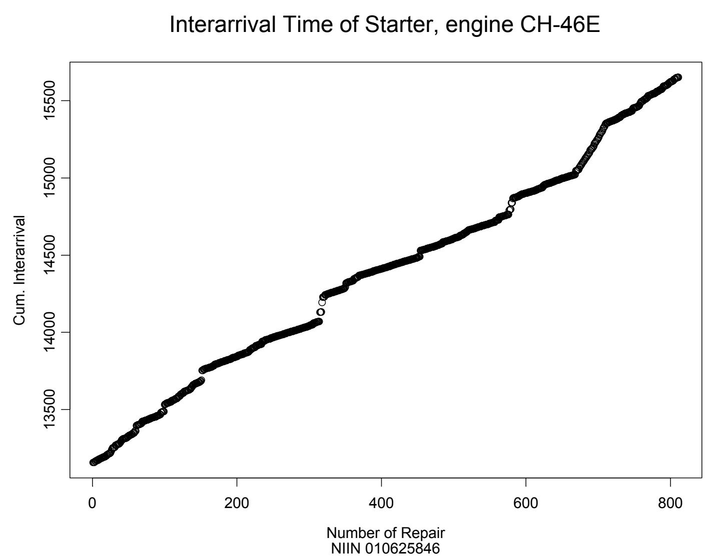

Figure 4. Cumulative Interarrival Times of Repairs Inducted of Starter Engine CH46-E.

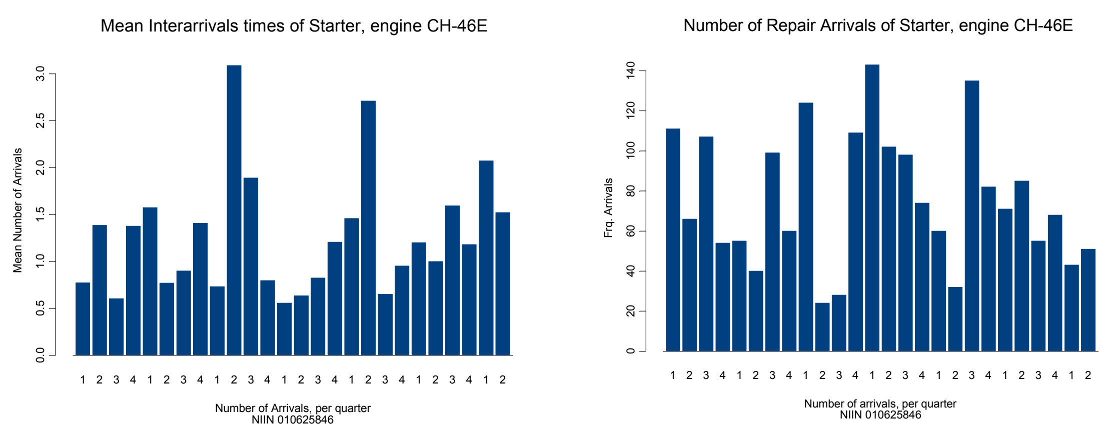

Figure 5. Histograms of the Mean and the Number of Arrivals of Starter Engine CH46-E for Repair.

D. THE CENSORING OF REPAIR TIMES

At the end of every quarter there are ongoing repairs that are not completed. For example, if an item is inducted into the repair system 226 days before the current quarter, its repair time can be represented as being more that 226 days. In statistical language, it is said that the repair time is right for this item “right censored” at 226 days.

In the UICP model, repair times are aggregated at the end of every quarter by their completion dates, instead of their induction dates. As a result of this aggregation, none of the repair times that are used have right censoring. However, repair times aggregated in this manner measure the time that it took to repair an item that completed its repair in the current quarter, not the time that it takes to complete a repair that is inducted in the current quarter. As we explain in Chapter 4, aggregation on the basis of completed repair times can lead to forecasts strongly affected by the nature of the arrival process.

LENGTH OF REPAIR TIME (RTAT) IN DAYS	NUMBER OF CENSORED REPAIRS
0 – 29	4688
30 – 59	2267
60 – 89	914
90 – 119	569
120 – 149	237
+ 150	1318

Table 3. Number of Censored Repairable Items between 1996 (1st Quarter) and 2002 (3rd quarter) in the Fifteen Selected Items, by Length of Repair Times in Days

The repair system has some variables that could bring a more transparent picture to the process. These variables would allow the calculation of state variables, such as the number of repairs under way and the amount of time they are still being processed. Table 3 shows the total number of repairs censored in the period of the analysis at DOPs, by length of repair time.

In conclusion, the development of a procedure that would require the storage of censored repair time would not impact the performance of the system because of the small amount of censored data that the system would have to process in comparison to the amount of data of repairs completed; further, the usage of the censored repair data can open a new source for investigation of the repair process.

III. UICP FORECAST

Although forecasts based on data are affected by uncertainty, a good forecast method should produce estimates that are close to the target of interest, without systematic biases. In this chapter, we introduce the UICP model, discuss some of the assumptions of the model, and examine its accuracy in predicting RTAT values for the following quarter.

A. UICP FORECASTING OF RTAT

The UICP model was implemented at NAVICP in the early 1960s. The current UICP methodology for forecasting RTAT uses a variety of statistical techniques for filtering, smoothing, estimation and, screening of outliers. A description of the details of the RTAT forecast model can be found in NAVSUP (1992). Accurate RTAT estimation is recognized as critical to the effective management of the Navy's supply system.

The UICP model predicts the performance of the repair system for future repairs in a "backwards" fashion, by using only the RTAT values for repairs that were completed at the end of a quarter. In other words, it attempts to predict the amount of time required for repair, given that the repair was completed at a future point in time, which is not the same as the amount of time required for repair, given that the repair was initiated at that same point in time. There are two fundamental differences between the two approaches:

1. A backward-looking forecast does not utilize information about repairs that are ongoing but not

completed at the end of a quarter. By contrast, a forward-looking forecast would attempt to utilize this information;

2. A backward-looking forecast is affected by the nature of the arrival process for repairs. For example, if no repairs were inducted into the repair system during the last 200 days, given that a repair has been completed today, we know that its RTAT value must be at least 200 days. By contrast, a forward-looking forecast is not affected by this factor.

B. THE ACCURACY OF UICP FORECASTS OF RTAT

An evaluation of UICP forecasts begins with measuring the magnitude of the error in quarters over time. Graphical comparisons of the forecast and the observed RTAT values are shown in Figure 6. The two plots display the two items with the highest number of repairs among the fifteen items. Plots are provided both for mean errors and the mean absolute error of forecast values.

The plot to the left for the first item (Servocylinder F/A 18) indicates some bias–in this case, a tendency to underestimate true RTAT values—while the plot on the right shows an approximately stationary absolute error over time. In the second row, there exist indications of autocorrelation in the data, probably because of more repair activity during certain circumstances such as war or major military exercises. The same pattern is seen for many of the items that were considered in this thesis research.

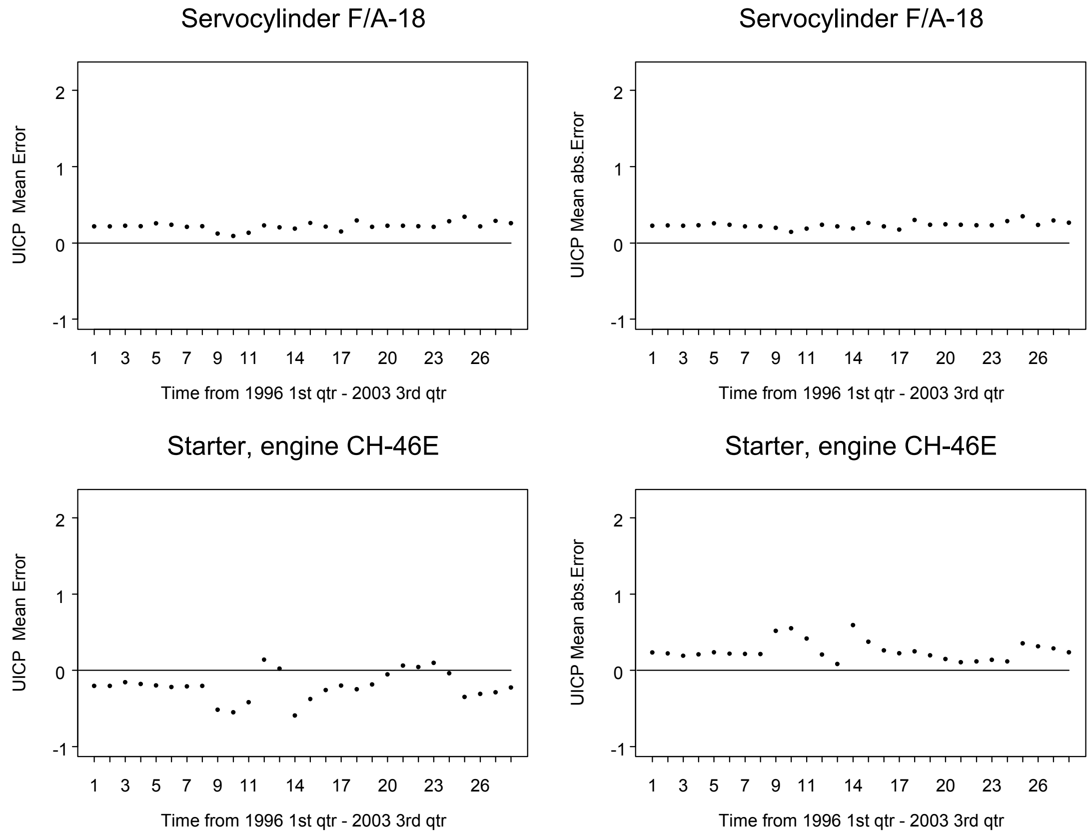

Figure 6. Quarterly Error of UICP Estimation of RTAT for Two of the Fifteen Selected Items.

Appendix D provides a complete set of graphs of this analysis.

C. SUMMARY

The UICP model produces RTAT forecasts that are oriented towards predicting the past performance rather than the future performance of the Navy’s repair system. In addition, its forecast values tend to be either systematically too high or too low for many, if not most, repairable items. This may be due in part to the outlier exclusion criteria used in the UICP model, or to the dependence of backward-looking repair times on the arrival process of repairs.

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IV. FORECAST ALTERNATIVES

This chapter will cover some possible alternatives for forecasting RTAT. First, a transformation of the original data that reduces the skewness of the distribution is sought, as a possible means of improving forecasts. Next, the effect on forecasting of aggregation of repair times by their completion dates is examined. For this purpose, the bootstrap is used to simulate the repair process for each item under consideration. This is done in two ways: assuming that repair arrivals are as given in the data and assuming that repair arrivals follow a Poisson process. Of interest is the effect that the arrival process has on the RTAT forecasts. Finally, a forecast method is developed based on aggregation of repair times by induction dates. This method has the advantage that RTAT forecasts are not affected by the nature of the arrival process; however, it must contend with the fact that at the end of every quarter there will be repairs in the system that have not been completed. These continuing repairs constitute “right-censored” RTAT values that must be incorporated into the forecasts. A technique is proposed for producing RTAT forecasts that uses both completed and right-censored RTAT values.

A. TRANSFORMATIONS OF REPAIR TIMES

An adequate transformation of the original data can provide good grounding for subsequent analyses. The difficulty is to determine which transformation is most appropriate for the data. The use of visualization tools such as quantile-quantile (QQ) plots can aid the search for the best transformation.

One of the reasons to try a transformation of the RTAT values is due to the criteria for outlier exclusion used by the UICP model in the calculation of RTAT forecast. The UICP criterion is based on the “fourth spread”, which is the difference between the first and third quartiles of the data used in estimation. Unlike typical exclusion rules that flag observations as outliers if they do not fall between the lower quartile minus 1.5 times the fourth spread, and the upper quartile plus 1.5 times the fourth spread (Devore, 2000), the UICP model multiplies the fourth spread by 1.0, which results in a larger number of observations being flagged as outliers (Ropiak, 2000).

Figure 7 shows histograms and normal QQ plots for repair times of one of the items in the data set used for this thesis research, both with and without a logarithm transformation. It is evident that the untransformed RTAT values have a strongly right-skewed distribution, and the logarithm of RTAT has a distribution that is closer to normal. Due to the skewness of RTAT values, the UICP outlier exclusion criterion operates mainly on the upper tail of the distribution.

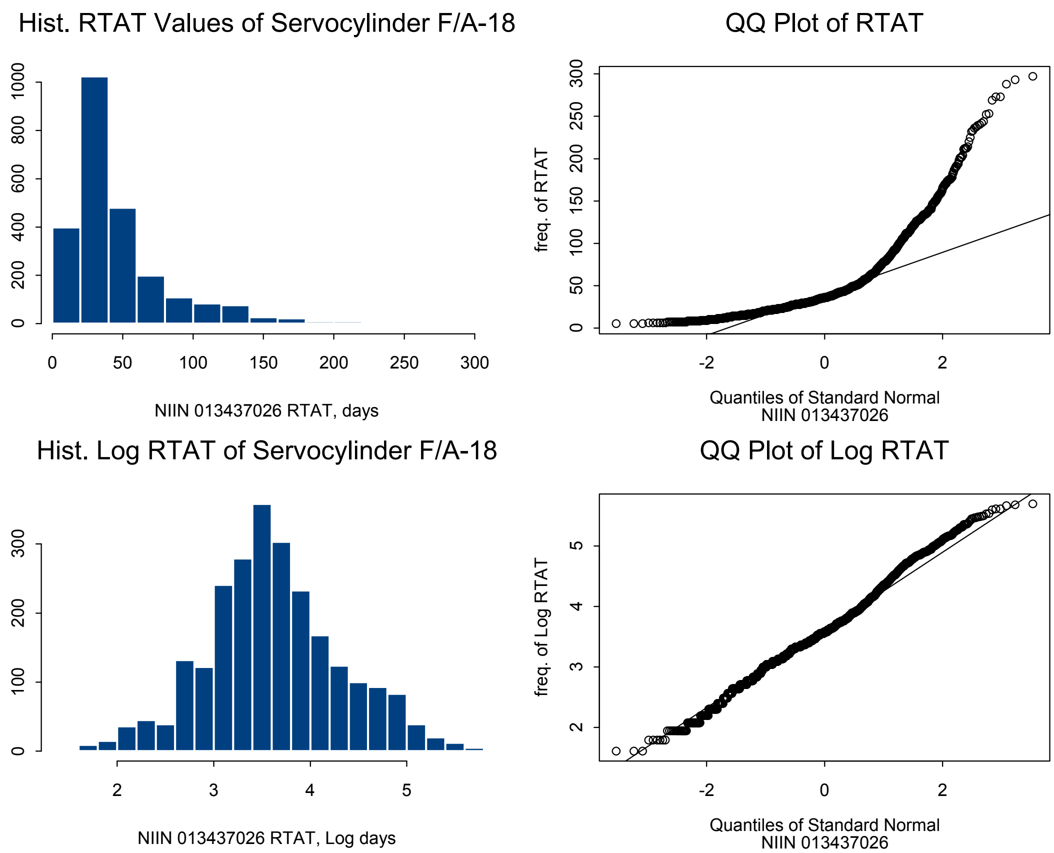

Figure 7. Histograms and Normal QQ-Plots of RTAT and Log of RTAT Values for the Servocylinder F/A-18.

The skewness of RTAT values that is evident in Figure 7 for the item shown is typical of Naval repairable item generally. Appendix E provides a complete set of histograms of the logarithm transformations across the fifteen items considered in this thesis research.

B. SIMULATION OF THE REPAIR PROCESS

In order to simulate the repair process for a particular item, the arrival times of repairs were calculated by subtracting RTAT from the completion times. Simulations were then conducted under two different scenarios. Under the first scenario, the arrival times were considered fixed, and repairs times were simulated by bootstrapping the actual repair times present in the data. Under the second scenario, arrival times were also simulated. The total number of repairs divided by the length of time frame under consideration was used as an estimate of the rate of a Poisson process for arrivals. This Poisson process produces, on average, nearly the same number of repairs as the process with fixed arrivals, but their occurrence is more uniform over the time frame under consideration; in other words, it is a process that has independent and stationary increments over time (Ross, 2000). Under both scenarios, RTAT values were aggregated on a quarterly basis according to their completion times, as is done under the UICP model.

The simulation was conducted separately for each of the fifteen items in the analyzed data. Each item had its own arrival process attributes, and the intention was to preserve them as much as possible. Each item is simulated 250 times and the following results were obtained for each of the 28 quarters for the years 1996 through 2002. These summaries consisted of the following statistics:

1. Mean number of repair completed within a quarter
2. Mean repair time within a quarter
3. Mean of the (natural) logarithm within a quarter
4. Standard deviation (SD) of the number of repairs completed within a quarter
5. SD of repair times within a quarter
6. SD of the logarithm of repair times within a quarter

In addition to these “within-quarter” summaries, a set of “between-quarter” summaries was also obtained:

1. SD of the means of repair times between quarters
2. SD of the means of the logarithms of repair times between quarters
3. Estimated coefficient of variation (CV) of the quantity in (1)
4. Estimated CV of the quantity in (2).

These within-quarters and between-quarter summaries were obtained for each item, both for the arrival processes as given in the data and under an assumption of a Poisson arrival process.

Under the simulation model used in the thesis research, all repair times for an item are collected into a single vector, and bootstrap samples are obtained from them. In other words, the repair process is treated as stationary with respect to repair time. Under a Poisson arrival process, quarterly mean repair times, aggregated on the basis of their completion times, should reflect this stationary repair process. However, the same may not be true for a general arrival process.

One of the outcomes of interest in the simulations is the magnitude of the between-quarter SD for RTAT (or the logarithm of RTAT) under the arrival process as given in the data, compared to a Poisson arrival process. Under a Poisson arrival process, it is expected that variability in mean RTAT between quarters should be determined primarily by the random variability of RTAT values themselves, and random Poisson fluctuations in the number of repairs completed in a quarter. Under a general arrival process, there is additional variability due to the arrival process itself. This additional variability will cause mean RTAT values to fluctuate more from quarter to quarter than the same repair process with Poisson arrivals. This additional variability may therefore cause the UICP forecast model to be responsive to factors that have nothing to do with the quality of the repair process. Table 4 provides the SDs and ratio between the SDs of the RTAT values generated by the two scenarios for all items.

DESCRIPTION OF THE ITEM	NIIN	SD OF RTAT FROM DATA (1)	SD OF RTAT FROM POISSON (2)	RATIO (1)/(2)
Navigational Unit 1	010543776	21.230	9.380	2.263
Inertial Navigational Unit	013870348	9.024	6.349	1.421
Stabilizer, optics	013000940	11.144	6.143	1.814
Gimbal assembly	010110855	54.652	16.484	3.315
Servocylinder	013513373	25.462	13.763	1.850
Servocylinder F/A-18	013437026	13.972	7.169	1.949
Helo rotor blade CH-53E	013163474	29.003	7.354	3.944
Module, film traction F/A-18	011542794	31.530	12.264	2.571
Gyroscope, displacement	009280072	18.973	3.210	5.911
Propeller	008871944	31.781	18.716	1.698
Power Supply LAU-7/A-5	011412735	4.126	2.701	1.528
Indicator, altitude	001655838	4.912	2.865	1.715
Nozzle, turbine Engine	004116264	15.995	14.124	1.132
Starter, engine CH-46E	010625846	27.912	12.893	2.165
Actuator assembly F404	011397177	14.752	11.227	1.314

Table 4. Standard Deviation (SD) for the Arrival from the Data, the Poisson Process, and the Ratio Between Two Items Among the Fifteen Selected.

Coefficients of variation (CVs) were calculated for the estimated between-quarter variances in order to measure the accuracy of the simulated quantities. The coefficient of variation is the estimated standard error (SE) of the quantity of interest divided by its mean. For the 250 bootstrap replications, the CVs for the estimated between-quarter SDs were never larger than 0.06 (6 percent), which demonstrates that the use of 250 bootstrap replication produced highly accurate estimates for our purposes.

Figure 8 displays two plots, based on the simulation experiment, that show fluctuations in mean RTAT corresponding to different items. In each plot, mean RTAT values for each quarter under the actual arrival times are shown as solid lines, while mean RTAT values under a Poisson process are shown as dotted lines. For the latter, 95% confidence bounds are also shown. The item that is plotted on the left (Gyroscope, displacement) exhibits little difference in fluctuations between quarters under the actual arrival process or under a Poisson process. The ratio of the between-quarters SDs (actual arrival versus a Poisson) was 1.70. By contrast, the item that is plotted on the right (Propeller) exhibits substantial difference, and the SD ration was 5.91. It is clear that a Poisson process cannot explain the entire fluctuation of the RTAT values. Appendix F brings the comparative graphs for all fifteen items selected.

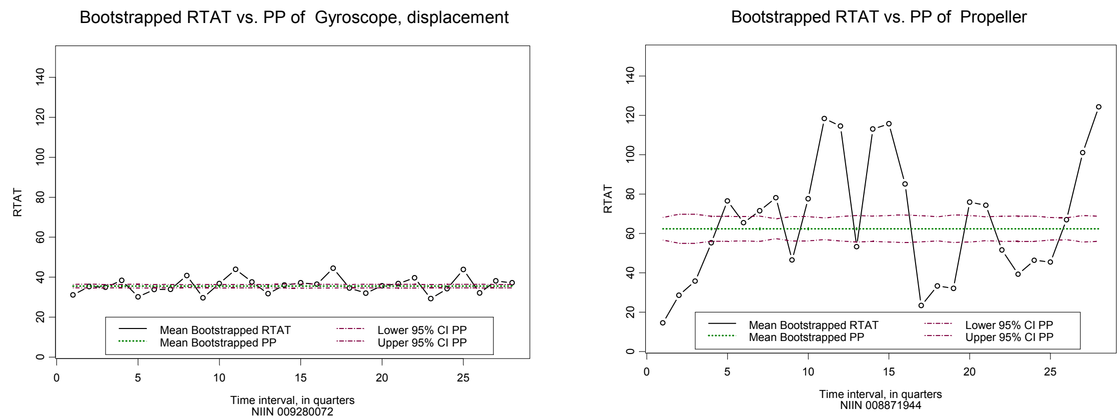

Figure 8. Mean RTAT Values of the Arrival Process and Mean RTAT Values Within a 95% Confidence Interval for an Idealized Poisson Process.

C. SURVIVAL FUNCTION

The accumulated time of a non-completed repair is valuable information about the state of the repair system when it is available. These right-censored repair times can be used in estimation of the survival function of the repair times, which is defined as $S(x) = 1 - F(x)$, where $F(x) = P(X \leq x)$ is the cumulative distribution function of the repair time (X). The survival function gives the probability that the repair will take at least x days (Conover, 1999).

The development of a forecast using the survival function requires the aggregation of repair time in a forward-looking fashion. The aggregation must be performed by the induction dates, similar to estimation in a queueing model where the time in the system or service time starts when the subject enters in the system. The system has to provide the data when a repair started.

Estimation of the survival function with aggregation by induction time was based on the following:

1. A framework *(FW)* of 30-day intervals (from zero up to 180 days, or two quarters): FW_i=*{30, 60, 90, 120, 150, 180}*, i = 1,..,6

2. Estimation of the survival function using the Kaplan-Meier estimate (Conover, 1999). Let $\hat{S}(X)$ denote the estimated survival function at time x.

3. A moving window of 365 days was adopted to update the estimated survival function to allow it to adapt to the most recent repair data, and to capture changes in the repair system such as the use of a new designated overhaul point.

Table 5 gives a comparison of the forecast accuracy for the method described above with the method currently used in the UICP model. Forecast accuracy was averaged across 27 quarters (excluding the first quarter of 1996) for which forecasts were calculated. It is seen that the proposed method has lower mean absolute errors for each of the fifteen items that were considered.

NOMENCLATURE	NIIN	ESTIMATES OF MEAN REPAIRTURN AROUND TIMES			
		SURVIVAL ANALYSIS METHOD		UICP Method	
		MEAN ERROR	MEAN ABS. ERROR	MEAN ERROR	MEAN ABS. ERROR
Navigational Unit 1	010543776	-0.063	0.312	-0.144	0.369
Inertial Navigational Unit	013870348	-0.110	0.310	-0.593	0.667
Stabilizer, optics	013000940	0.092	0.234	-0.326	0.486
Gimbal assembly	010110855	0.189	0.747	0.582	0.919
Servocylinder	013513373	-0.004	0.491	-0.138	0.634
Servocylinder F/A-18	013437026	0.108	0.336	0.405	0.418
Helo rotor blade CH-53E	013163474	-0.012	0.399	0.632	0.641
Module, film traction F/A-18	011542794	0.171	0.661	0.084	0.688
Gyroscope, displacement	009280072	0.005	0.228	0.169	0.232
Propeller	008871944	0.314	0.466	0.828	0.872
Power Supply LAU-7/A-5	011412735	0.004	0.183	-0.157	0.258
Indicator, altitude	001655838	0.055	0.231	-0.399	0.506
Nozzle, turbine Engine	004116264	-0.082	0.36	0.449	0.533
Starter, engine CH-46E	010625846	0.118	0.394	0.023	0.473
Actuator assembly F404	011397177	0.165	0.303	0.53	0.537

Table 5. Mean Error and Mean Absolute Error of the Forecasts Using Survival Function and UICP for the Fifteen Selected Items.

Appendix G provides a complete set of graphs that summarizes forecasts error using the proposed method based on estimation of the survival function.

V. CONCLUSION

A. INTRODUCTION

This chapter revisits the research questions, and presents some conclusions and recommendations for future research studies.

B. RESEARCH QUESTIONS AND RESULTS

The following research questions were addressed based on results observed from the analysis of the repair times for the fifteen Naval inventory items selected:

1. Which probabilistic assumptions remain valid for the RTAT?

It was found that the distributions of repair times were usually strongly skewed to the right. In other words, there is a prominent right tail of long repair times for most of the items considered. This skewness has implications for forecasting, as further discussed below. Approximately 90% of the repairs can be completed within a quarter or in 90 days.

For most items, the arrival process for repairs is not stationary, nor does it resemble a Poisson process. Under the current UICP forecast methodology, this factor can lead to large prediction errors for RTAT.

2. If the forecast were modified to include the repairs under way, how much better would the forecast be?

An alternative model for forecasting RTAT values, based on aggregation of repairs by their induction dates instead of their completion dates (as is done by the UICP model), can make use of repairs under way but can not be completed at the time that forecasts are calculated. Accumulated time in the repair system is treated as a right-censored repair time. Censored and uncensored data can be used together using survival analysis techniques. It was found that a new forecasting method based on survival analysis can provide more accurate forecasts than the current UICP model for forecasting RTAT.

3. Is the current RTAT forecast methodology based on an appropriate measure of performance for the Naval inventory repair system?

RTAT forecasts are an input to the UICP model, which is used to manage inventory levels for the Naval supply system. When material enters the repair system in NRFI condition, there is a deficit that must be covered by the supply system. The state of the repair system at the time that repairs are inducted provides information about the time needed for NRFI material to be returned to inventory in RFI condition. It is, therefore, appropriate for the forecasting of RTAT to be based on the induction times of repairs, instead of the completion times currently done by the UICP model. In addition to describing the “past” of the repair process, aggregation on completion times causes the forecasts to be affected by variability due to the repair arrival process, which as noted above cannot always be characterized as a Poisson process.

C. RECOMMENDATIONS

A transformation such as the logarithm can reduce the skewness of RTAT values and make it more appropriate for forecasting with an outlier exclusion criterion.

Alternatively, one could search for individual transformation and identify the best for groups of items.

The simulation study undertaken as part of the thesis research provides evidence that substantial variability in the UICP forecasts of RTAT is not due to variability in the repair process. It is, however, due to the variability introduced by the repair arrival process. For most items, it would not be appropriate to use a Poisson process to describe these arrivals.

Aggregating repairs by their induction dates can be reduced the variability from the arrival process, instead of by their completion dates. In order to do this, it is necessary to use data on repairs that have been inducted but that not have been completed at the time that forecasts are calculated. Survival analysis techniques can be used for estimating both censored and uncensored repair times. The computation of mean absolute error showed that an estimation using these techniques produced more accurate forecasts for the fifteen items considered than the current UICP methodology.

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APPENDIX A. REPAIRABLE ITEMS SELECTED

Table A.1 displays a list of the fifteen NIINs and names selected for this thesis analysis. These items, identified in Ropiak (2000), had high monetary value and high repair rates.

NATIONAL ITEM IDENTIFICATION NUMBER – NIIN	NOMENCLATURE
010543776	Navigational Unit 1
013870348	Inertial Navigational Unit
013000940	Stabilizer, optics
010110855	Gimbal assembly
013513373	Servocylinder
013437026	Servocylinder F/A-18
013163474	Helo rotor blade CH-53E
011542794	Module, film traction F/A-18
009280072	Gyroscope, displacement
008871944	Propeller
011412735	Power Supply LAU-7/A-5
001655838	Indicator, altitude
004116264	Nozzle, turbine engine
010625846	Starter, engine CH-46E
011397177	Actuator assembly F404

Table A1. List of the Fifteen NIIN and Their Name Descriptions.

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APPENDIX B. NAVICP-PHI DATA SET (1996-2002)

Table B1 below displays the data field and describes each field of the repairs records and table B2 for the forecasts of the UICP model.

RECORD FIELD	DESCRIPTION
D046	NIIN – National Identification Number.
C001A	Family Group Code (FGC).
C001B	Family Relationship Code (FRC).
K002	Document (repair transaction TIR).
SEQ_NO	Sequence Number of the Repair Document.
QTY	Quantity of the units recorded on the repair transaction TIR.
TATOBS	Total repair bench time (induction into 'M' condition until completion into 'A' condition).
COMP_DT	Completion date (date on transaction TIR for repair completion into 'A" condition).
DOP	Repair facility (Organic/Commercial/DMISA).
GDAYS	Subset of time accounting for the number of days item was reported in 'G' or awaiting parts time not physically in repair….this amount is accounted for in the total TAT time (TATOBS).
INDUCT_DT	Date item was inducted into 'M' condition.
ARAS	Code to designate repair transaction entered system via the commercial reporting system of CAMS (C) or CAV (V).
EXCLUDE_IND	Indicator 'P' identifies that the item was coded as an exclusion or outlier using the UICP logic of comparing the TATOBS value to the file forecast value. (If TATOBS value is <20% or >200% of the file value of that quarter, it is considered an outlier.) Outliers are excluded from all Math calculations to determine the new file forecast.
REV_DAYS	Value used by the UICP system in the math calculations for the new forecast value.

Table B1. List Names of Fields and Their Descriptions.

RECORD FIELD	DESCRIPTION
NIIN	National Item Identification Number
COG	Only 7R items
MCC	Material Control Code
FGC	Family Group Code
FRC	Family Relationship Code
Quarterly_Demand	Demand Total within the Quarter
B010	Average Contract Production Lead-time Forecast
B011A	Contract Procurement Lead-time Forecast
F007	Wear out Rate
F009	Survival Rate
B012E	RTAT (Repair Turn-around Time) Average Bench Time Forecast + administrative additive

Table B2. List Names of Fields and their Description of the Data produced by UICP Forecast Model.

Table B3 displays sets of data that were available from the NAVICP-PHI of observed Repair Turnaround Time values:

Period	Data size
1996	126,758 records
1997	160,677 records
1998	161,886 records
1999	156,809 records
2000	171,759 records
2001	177,445 records
2002	186,609 records†

Table B3. RTAT Values from NAVICP-Phi

†partial file, December not included

Table B4 displays the data set Forecasts of RTAT available for this research from the UICP model:

YEAR	DATA AVAILABLE			
	1st QUARTER	2nd QUARTER	3rd QUARTER	4th QUARTER
1995	-	-	69,211	69,308
1996	68,633	68,919	69,195	68,938
1997	68,935	69,005	69,145	69,249
1998	69,072	69,436	69,422	69,272
1999	68,940	68,914	68,815	68,712
2000	68,841	68,942	69,154	69,136
2001	69,280	69,023	68,197	68,457
2002	68,522	68,559	68,509	-

Table B4. Data Sets Forecast of RTAT from UICP model.

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APPENDIX C. HISTOGRAMS OF RTAT

Figure C1 displays observed RTAT values in the fifteen selected items. As it shows, the shapes of the distribution of RTAT is remarkably right skewed.

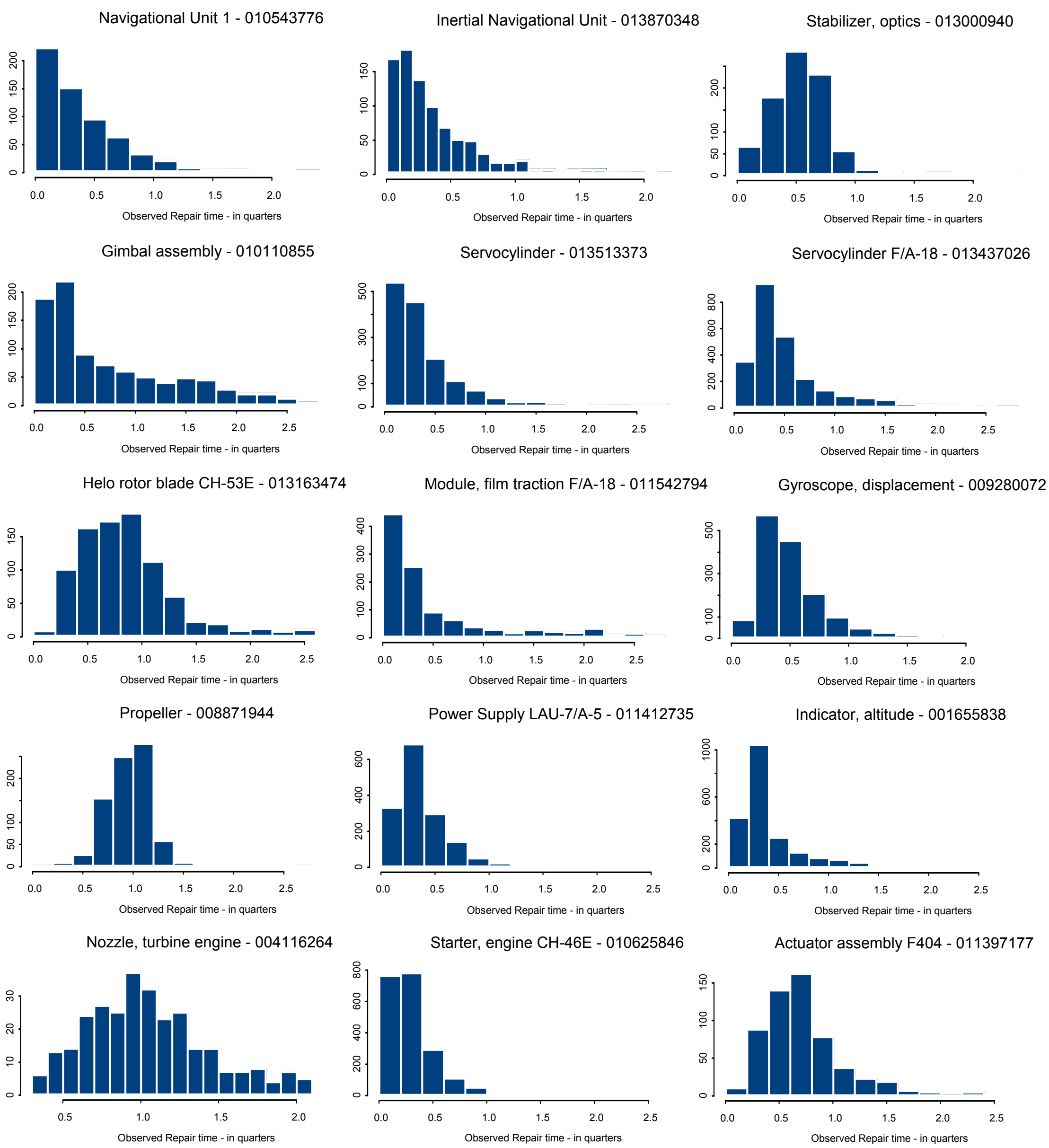

Figure C1. Histograms of Observed RTAT Value on the Fifteen Selected Items.

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APPENDIX D. UICP ERRORS IN FORECASTING

The following graphs display the observed RTAT values and the UICP forecasts for the fifteen selected items.

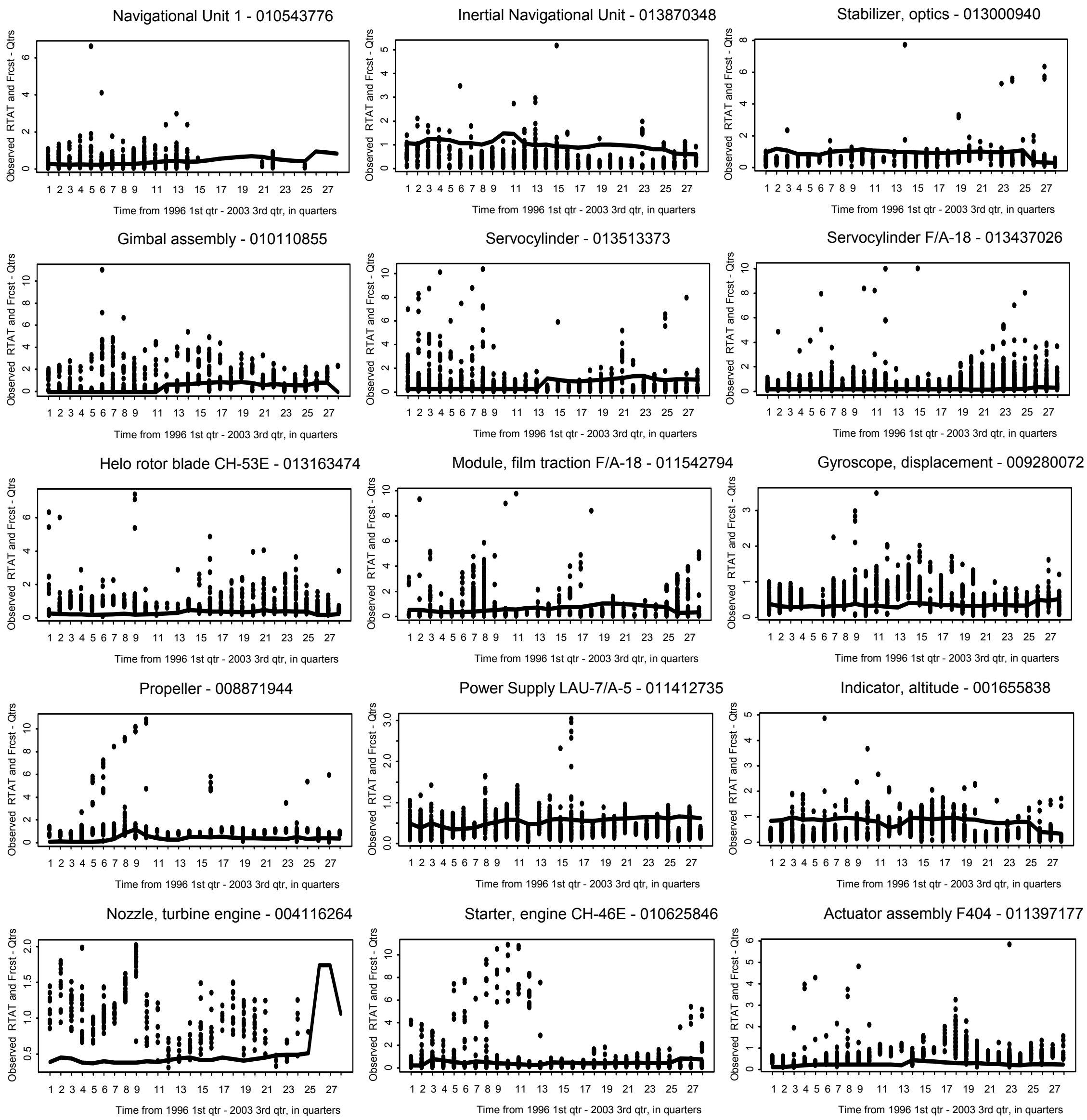

Figure D1. UICP Forecast of RTAT vs. Observed RTAT Values for the Fifteen Items.

Figure D1 shows that the UICP forecasts of RTAT values have bias in estimating RTAT value; the model typically underestimates or overestimates RTAT values. Figure D2 shows that the error in estimation is not stationary which suggest the presence of autocorrelation for almost all items.

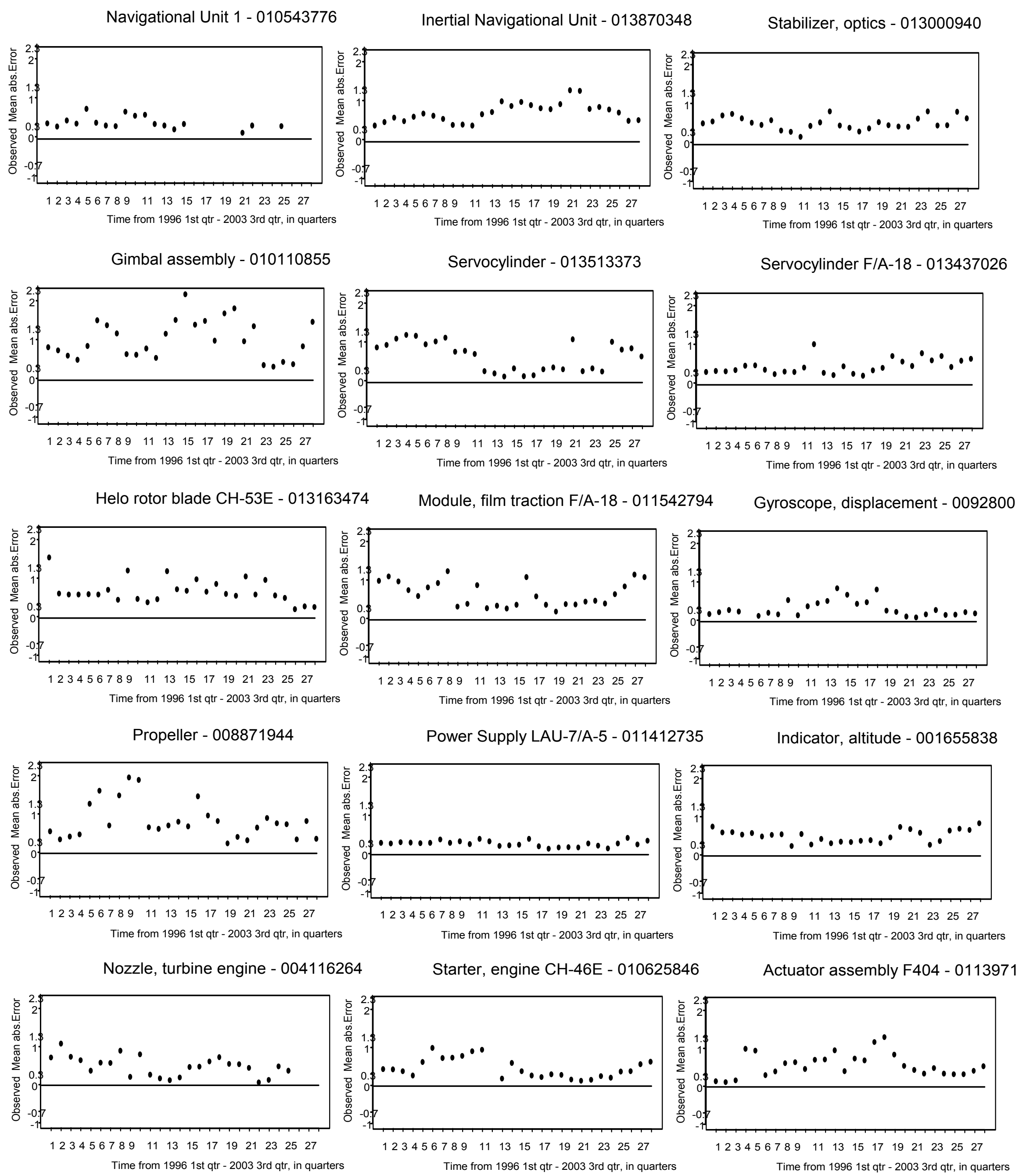

Figure D2. Mean Absolute Error of UICP Forecast Values for the Fifteen Items.

APPENDIX E. FORECAST ALTERNATIVES – NATURAL LOGARITHM OF RTAT VALUES

Logarithm transformation of RTAT values can symmetrically distribute the majority of RTAT values, as shown in Figure E1. Therefore, better estimates can be provided using the natural logarithm of the original data.

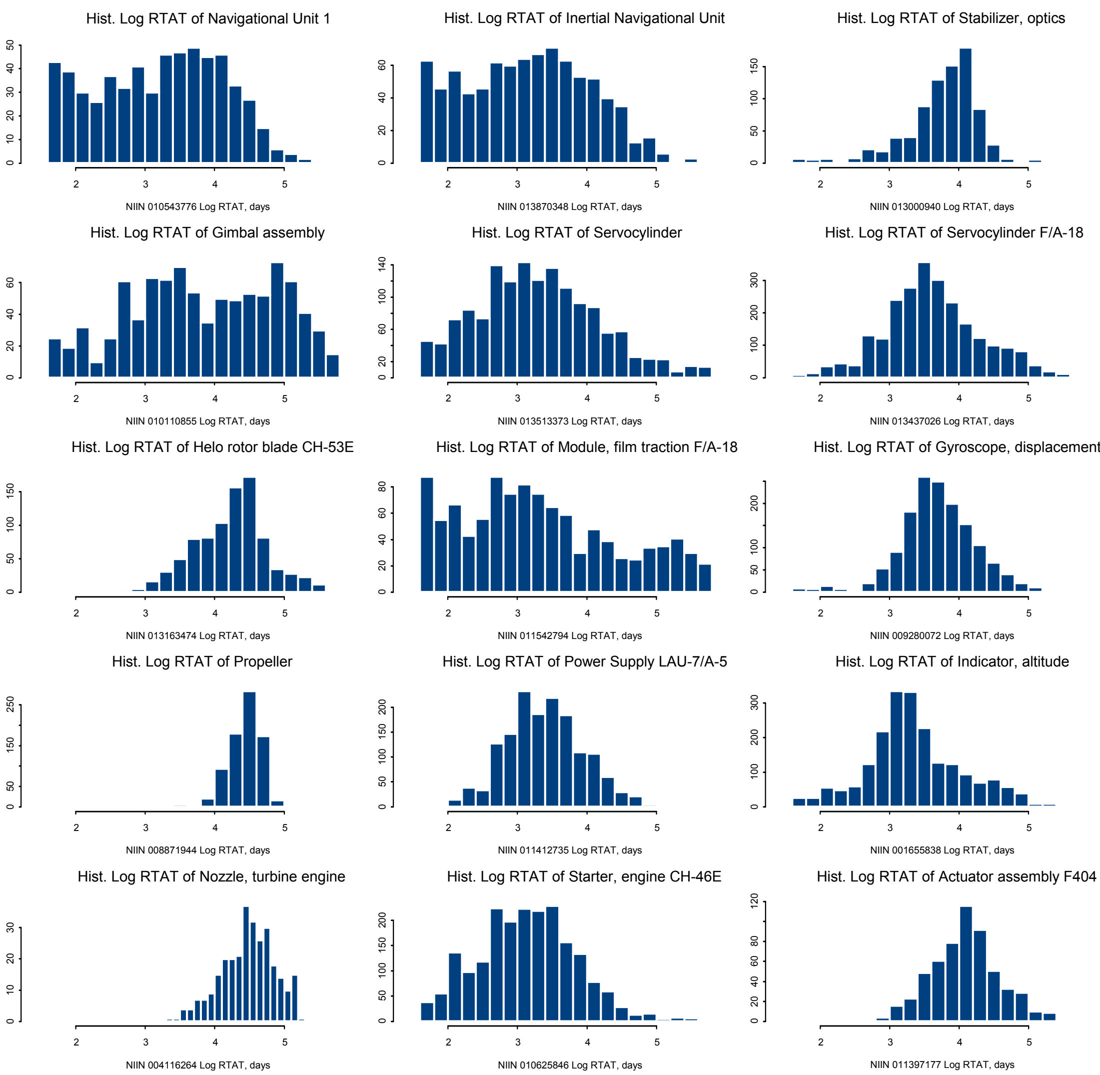

Figure E1. Histograms of Natural Logarithm of RTAT Values for the Fifteen Selected Items.

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APPENDIX F. FORECAST ALTERNATIVES - SIMULATION OF THE REPAIR ARRIVALS AND THE POISSON ARRIVALS

Figure F1 displays a graphical result of the bootstrapped simulation for both the arrival process and an ideal arrival Poisson process; the graphs provide a 95% confidence interval for the Poisson process.

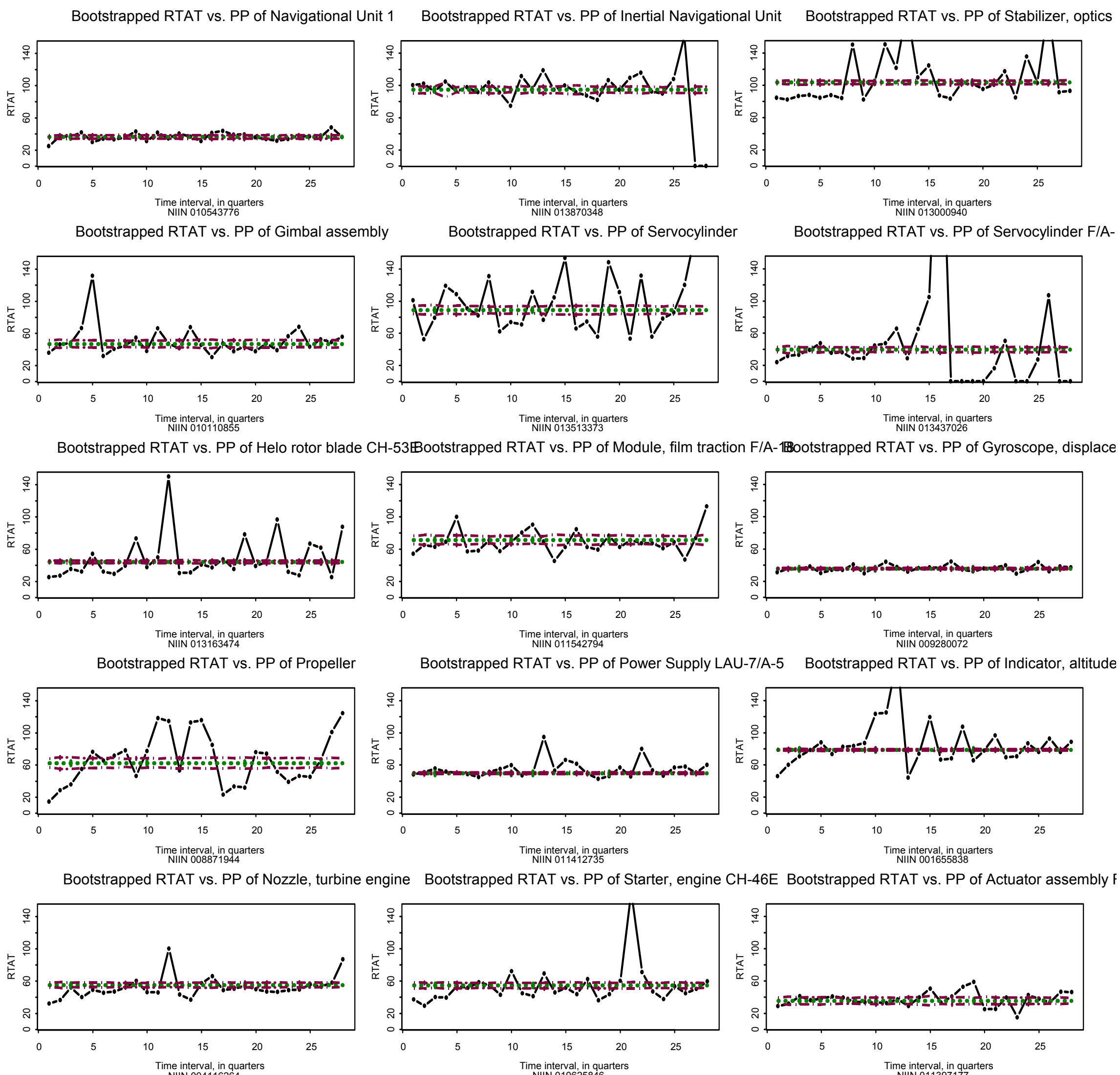

Figure F1. Mean RTAT Values Bootstrapped from the Arrival Process and Mean RTAT Values Within a 95%

Confidence Interval for a Bootstrapped Ideal Arrival Poisson Process (PP).

S-Plus® coded function used for developing the simulation of bootstrap simulation of the RTAT values:

```
function(Xdata, nvec, nboot, useseed = NULL)
{
########################################################################
#                                                                      #
#     Function performs a Bootstrap sample, computes the estimates    #
#           for the mean and standard deviation for the Bootstrap     #
#           of the arrival process as it is and the log of the data   #
#           and the mean and variance for the the Poisson arrival     #
#           and the log of the Poisson arrival.
#
#     Parameters:
#     Xdata = data frame with columns named with a set of observed
#           repair times from where a bootstraing is going to be
#           performed. the data set has indentical and independent
#           observations. the data set hase at least the columns:
#
#     NIIN        =     National Individual Identification Number;
#     TAT         =     observed reapir time;
#     COMP.JUL=   julian date of the end of repair.
#     nvec  =     vector of niin values for which bootstrap
#                 is desired
#     nboot =     number of bootstrap replications per niin
#
#     Return:
#     list of data frames of the results from the Bootstrap.
#                                                                      #
# RAK  5-9-03 (modified 5-21-03)                                       #
#                                                                      #
########################################################################

if(!is.null(useseed))
           .Random.seed <- useseed
nn    <- length(nvec)
Y     <- matrix(0, 28 * nn, 7)
sdb   <- matrix(0, nn, 3)
Yp    <- Y
dimnames(Y)       <- list(NULL, c("NIIN", "MEANSAMP", "MEANTAT",
                         "MEANLOG", "SDSAMP", "TAT.W", "LOGTAT.W"))
dimnames(sdb)     <- list(NULL, c("NIIN", "TAT", "LOGTAT"))
sdpb        <- sdb
sdbvar      <- sdb
sdpbvar     <- sdb
ds          <- julian(12, 31, 2002) - julian(01,01, 1996)
d0          <- julian(01, 01, 1995)
d1          <- julian(12, 31, 2002)
for(kk in 1:nn)
{
      tt    <- Xdata[, "NIIN"] == nvec[kk]
      ntt   <- sum(tt)
```

```
tatvec<- Xdata[tt, "TAT"]
logvec      <- log(tatvec)
datevec <- Xdata[tt, "COMP.JUL"] - tatvec
cvec  <- month.day.year(datevec)[[3]]
lambda      <- (ntt * (d1 - d0))/ds
nv    <- 0
npv   <- 0
nc    <- numeric(28)
ncp   <- nc
for(j in 1:nboot)
{
      a     <- sample(ntt, ntt, replace = T)
      cvec  <- datevec + tatvec[a]
      quartvec<- as.numeric(quarters(cvec))
      mvec  <- 4 * (month.day.year(cvec)[[3]] - 1996) + quartvec
      yvec  <- matrix(NA, 28, 2)
      for(i in 1:28)
      {
            tt <- mvec == i
            if(any(tt)>0)
            {
              ik <- 28 * (kk - 1) + i
              Y[ik, 2]  <- Y[ik, 2] + sum(tt)
              Y[ik, 3]  <- Y[ik, 3] + sum(tatvec[a][tt])
              Y[ik, 4]  <- Y[ik, 4] + sum(logvec[a][tt])
              Y[ik, 5]  <- Y[ik, 5] + sum(tt)^2
              if(sum(tt) > 1)
              {
                nc[i]   <- nc[i] + 1
                Y[ik, 6]      <- Y[ik, 6] + var(tatvec[a][tt])
                Y[ik, 7]      <- Y[ik, 7] + var(logvec[a][tt])
              }
              yvec[i, 1]      <- mean(tatvec[a][tt])
              yvec[i, 2]      <- mean(logvec[a][tt])
            }
      }
      vv <- !is.na(yvec[, 1])
      if(sum(vv) > 1)
      {
            nv          <- nv + 1
            b           <- var(yvec[vv, 1])
            sdb[kk, 2]  <- sdb[kk, 2] + b
            sdbvar[kk, 2]     <- sdbvar[kk, 2] + b * b
            b           <- var(yvec[vv, 2])
            sdb[kk, 3]  <- sdb[kk, 3] + b
            sdbvar[kk, 3]     <- sdbvar[kk, 3] + b * b
      }
      k     <- rpois(1, lambda)
      a     <- sample(ntt, k, replace = T)
      cvec  <- floor(runif(k, d0, d1)) + tatvec[a]
      quartvec<- as.numeric(quarters(cvec))
      mvec  <- 4 * (month.day.year(cvec)[[3]] - 1996) + quartvec
      yvec <- matrix(NA, 28, 2)
      for(i in 1:28)
      {
            tt <- mvec == i
            if(any(tt)>0)
```

```
                {
                  ik        <- 28 * (kk - 1) + i
                  Yp[ik, 2]       <- Yp[ik, 2] + sum(tt)
                  Yp[ik, 3]       <- Yp[ik, 3] + sum(tatvec[a][tt])
                  Yp[ik, 4]       <- Yp[ik, 4] + sum(logvec[a][tt])
                  Yp[ik, 5]       <- Yp[ik, 5] + sum(tt)^2
                  if(sum(tt) > 1) {
                    ncp[i]  <- ncp[i] + 1
                    Yp[ik, 6]     <- Yp[ik, 6] + var(tatvec[a][tt])
                    Yp[ik, 7]     <- Yp[ik, 7] + var(logvec[a][tt])
                  }
                  yvec[i, 1]      <- mean(tatvec[a][tt])
                  yvec[i, 2]      <- mean(logvec[a][tt])
                }
          }
          vv <- !is.na(yvec[, 1])
          if(sum(vv) > 1)
          {
                npv         <- npv + 1
                b           <- var(yvec[vv, 1])
                sdpb[kk, 2]       <- sdpb[kk, 2] + b
                sdpbvar[kk, 2]    <- sdpbvar[kk, 2] + b * b
                b           <- var(yvec[vv, 2])
                sdpb[kk, 3]       <- sdpb[kk, 3] + b
                sdpbvar[kk, 3]    <- sdpbvar[kk, 3] + b * b
          }
          if(50 * floor(j/50) == j)
                cat("Finished NIIN ", kk, " iteration ", j, "\n")
          }
    sdb[kk, 2:3]  <-sdb[kk, 2:3]/nv
    sdbvar[kk,2:3]<-sqrt(sdbvar[kk,2:3]/nv-sdb[kk,2:3]^2)/
(sqrt(nv) * sdb[kk, 2:3])
    sdb[kk, 2:3]   <- sqrt(sdb[kk, 2:3])
    sdpb[kk, 2:3]  <- sdpb[kk, 2:3]/npv
    sdpbvar[kk,2:3]<-sqrt(sdpbvar[kk,2:3]/npv-sdpb[kk,2:3]^2)/
(sqrt(npv) * sdpb[kk, 2:3])
    sdpb[kk, 2:3]  <- sqrt(sdpb[kk, 2:3])
    ilo            <- 28 * (kk - 1) + 1
    ihi            <- 28 * kk
    Y[ilo:ihi, 6]     <- sqrt(Y[ilo:ihi, 6]/nc)
    Y[ilo:ihi, 7]     <- sqrt(Y[ilo:ihi, 7]/nc)
    Yp[ilo:ihi, 6]    <- sqrt(Yp[ilo:ihi, 6]/ncp)
    Yp[ilo:ihi, 7]    <- sqrt(Yp[ilo:ihi, 7]/ncp)
    for(i in 1:28)
    {
          ik    <- 28 * (kk - 1) + i
          Y[ik, 1]<- kk
          if(Y[ik, 2] > 0) {
                Y[ik, 3:4]  <- Y[ik, 3:4]/Y[ik, 2]
                Y[ik, c(2, 5)]    <- Y[ik, c(2, 5)]/nboot
                Y[ik, 5]    <- sqrt(Y[ik, 5] - Y[ik, 2]^2)
          }
          if(Yp[ik, 2] > 0) {
                Yp[ik, 3:4]       <- Yp[ik, 3:4]/Yp[ik, 2]
                Yp[ik, c(2, 5)] <- Yp[ik, c(2, 5)]/nboot
                Yp[ik, 5]   <- sqrt(Yp[ik, 5] - Yp[ik, 2]^2)
          }
```

```
      }
      cat("*** FINISHED NIIN ", kk, "\n")
}
sdb         <- data.frame(nvec, sdb[, 2:3])
names(sdb)[1]     <- "NIIN"
sdpb        <- data.frame(nvec, sdpb[, 2:3])
names(sdpb)[1]    <- "NIIN"
sdbvar      <- data.frame(nvec, sdbvar[, 2:3])
names(sdbvar)[1]<- "NIIN"
sdpbvar     <- data.frame(nvec, sdpbvar[, 2:3])
names(sdpbvar)[1]<- "NIIN"
nlist       <- nvec[Y[, 1]]
Y           <- data.frame(nlist, Y[, 2:7])
names(Y)[1]       <- "NIIN"
Yp          <- data.frame(nlist, Yp[, 2:7])
names(Yp)[1]      <- "NIIN"
return(list(Y = Y, Yp = Yp, sdb = sdb, sdpb = sdpb, sdbcv = sdbvar,
      sdpbcv = sdpbvar))
}
```

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APPENDIX G. FORECASTING ALTERNATIVES – SURVIVAL FUNCTION

Figure G1 shows the observed RTAT values and forecasts using the survival functions estimates. Notably, the estimates trace the distribution of the data more often than the UICP forecasts does.

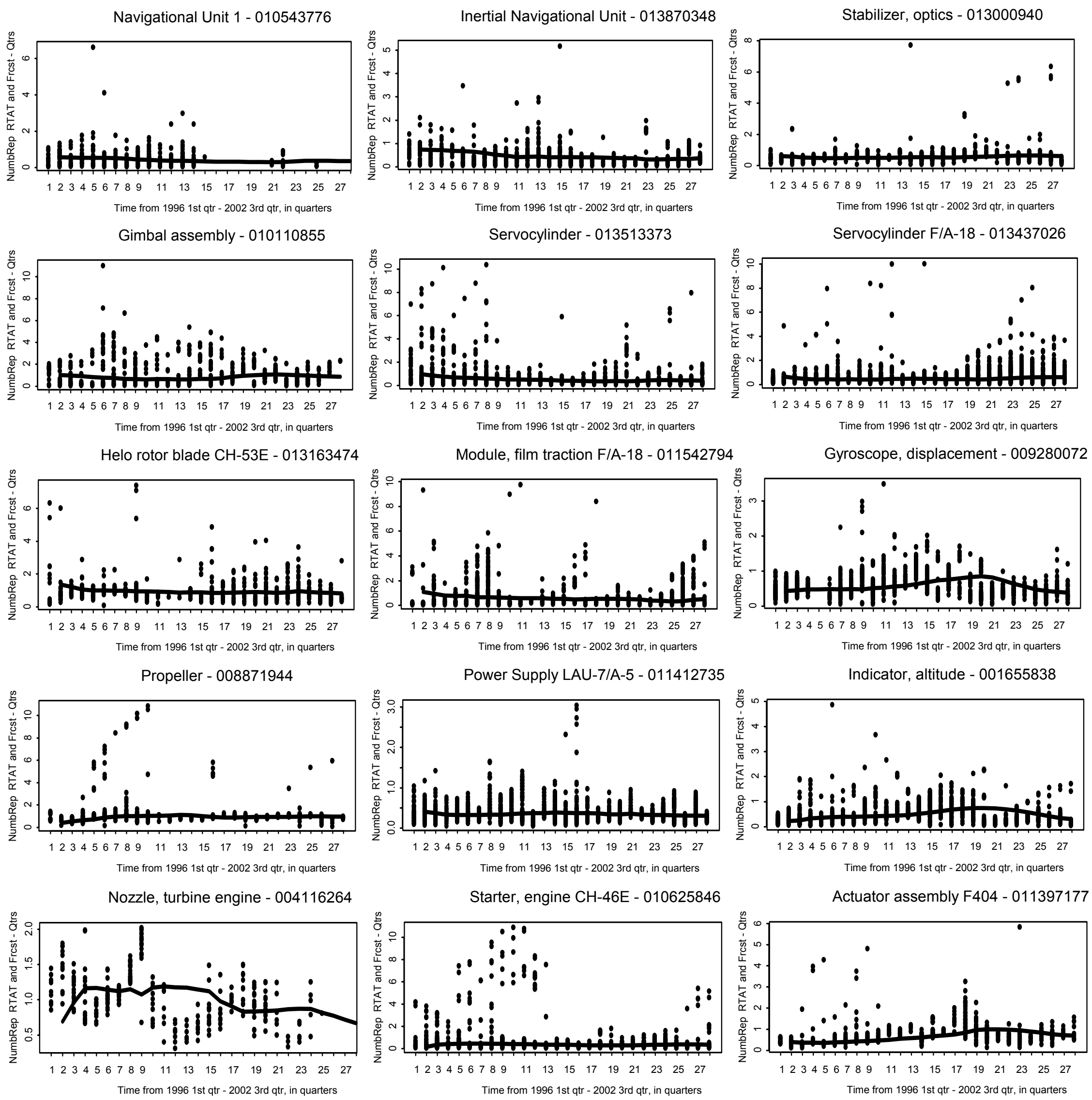

Figure G1. Survival Function Forecast Values vs. Observed RTAT Values for the Fifteen Items.

Figure G2 displays the mean absolute error and the forecasts of the survival function. The error in estimation is approximate zero and homogenous and the magnitude of the autocorrelation is minor with this method in comparison with the current method used by UICP.

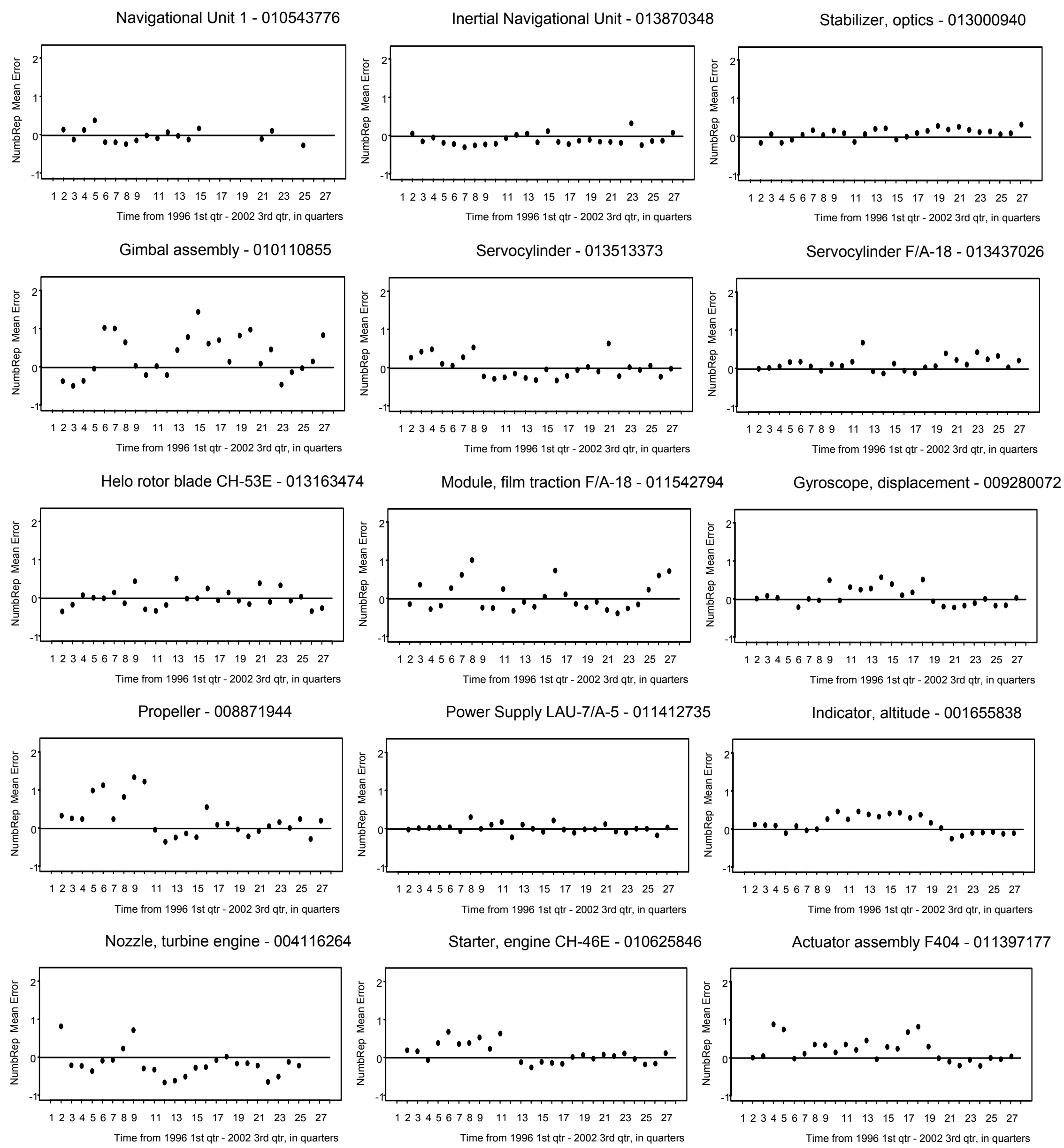

Figure G2. Mean Error of the Estimation Using Survival Function for the Fifteen Items.

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